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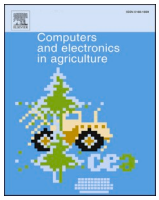

Original papers

Classifying season long livestock grazing behavior with the use of a low-cost GPS and accelerometer

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ABSTRACT

Remote tracking of livestock through the use of GPS technology has tremendous potential for the study of livestock use patterns on the landscape. The addition of high frequency accelerometers on GPS units has potential to give researchers and managers the capability of accurately partitioning GPS points into differing behaviors, providing further insight into livestock grazing selection, pasture use, and changes in forage preference through time. Most studies to date have examined the use of GPS collars with accelerometers on small pastures and over relatively short time periods; evaluation of this technology is needed on larger pastures over extended time periods. The objective of this study was to test the effectiveness of predicting season-long livestock behavior through the use of a low-cost, non-commercial, lab-constructed GPS collar outfitted with a high frequency 3-axis accelerometer. Collars were deployed on yearling steers continuously grazing native grassland pastures for 3 months. GPS devices were set to record a fix at 1-minute intervals. Accelerometers were programmed to record X, Y, and Z positions at 12 Hz (12 records per second). The accelerometer data was aggregated to 1 s intervals initially, and mean, minimum, maximum, and standard error of X, Y, and Z axes were calculated between the start and stop time of each GPS fix. Additional metrics were calculated from the GPS fix data to include rate of travel and stationary point identification to aid in classification. Direct visual observations of cattle wearing the GPS collars were recorded for numerous time periods each grazing season to provide data for classifying GPS data into graze and non-graze behaviors. Several classification algorithms were tested to assess misclassification rates and predict behavior of unobserved data. Overall misclassification rate was lowest for a random forest model (11.2%). Time spent grazing ranged from 8.67 to 10.49 h daily, and timing of grazing tended to be heaviest during morning and evening hours, both of which were expected from yearling steers grazing native pasture in the summer. These results show there is great promise in using accelerometer-equipped GPS collars to accurately identify livestock grazing locations, which could benefit researchers and land managers monitoring rangeland use.

1. Introduction

The ability to characterize animal behavior within spatial and temporal context on the landscape is a major benefit provided by Global Positioning System (GPS) technology. The use of GPS tracking to monitor free ranging livestock movement and use patterns has been well established with over 99 studies since 1997 (Anderson et al. 2012). One of the main benefits to using GPS data is the ability to continuously monitor cattle locations and pair locations with numerous spatial parameters stored in a geographic information system (Putfarken et al. 2008). Previous research has demonstrated the use of GPS technology to study strategies to improve livestock distribution through placement of low moisture blocks and salt (Bailey et al. 2008), the relation of forage nitrogen content to livestock distribution (Zengeya et al. 2013), and the influence of cattle genetics on animal distribution in terms of distance to water and elevation (Bailey et al. 2015). Most of the past research utilizing GPS tracking of cattle has been used to describe livestock distribution; fewer GPS tracking studies, however, have aimed to describe factors that drive livestock grazing behavior.

Quantifying grazing behavior and locations of free ranging animals can be difficult, especially on rugged and/or remote rangelands. Commercially available livestock tracking devices often include motion sensor activity which can be used to build classification models for predicting cattle behavior such as grazing, standing/resting, or

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Fig. 1. GPS collar construction. Collar components include: A) 3-axis X16 mini accelerometer manufactured by Gulf Coast Concepts, LLC, B) iGotU GT-120 GPS data logger, and C) 5200 mAh lithium ion batteries. All components were attached to a PVC plate, cut to fit tightly within a Pelican 1020 micro-case. Batteries and GPS unit were secured in place using Velcro straps, the accelerometer was attached to the plate using nuts and bolds. Pelican cases were attached to a Nylon cow collar using tape and cable ties (right image).

travelling (Ungar et al. 2011, Augustine and Derner 2013). Commercially available livestock tracking devices, however, are expensive, and often cost prohibitive for both researchers and producers alike. These devices may also lack the temporal precision necessary to accurately predict behavior (e.g. minimum fix times of 5 min). GPS tracking devices built using low-cost datalogger components have been shown to be effective in tracking cattle at a substantially reduced cost and improved temporal precision compared to commercially available GPS collars (Knight et al. 2018, McGranahan et al. 2018). The inclusion of motion sensing sensors to these low cost GPS tracking devices can provide additional data necessary to accurately predict season long livestock behavior.

High frequency accelerometers measure acceleration (motion) forces in 3-axes and have been used to study behavior in wildlife and livestock species (Brown et al. 2013, Bailey et al. 2008). The combination of GPS technology and high frequency accelerometers has great potential for discriminating livestock behaviors by continuously monitoring an animal's movement and velocity. Inferences of behavior can improve our understanding of foraging patterns and strategies as they relate to landscape features. Though previous research utilizing high frequency accelerometer data has demonstrated the ability of this technology to accurately predict livestock behavior, study lengths are often limited to a few days or weeks, and have yet to be tested throughout season-long livestock grazing (Gonzalez et al. 2015, Mansbridge et al. 2018). The goal of this project was to develop and test an algorithm to monitor and predict season-long livestock grazing behavior on rangelands using data obtained from low-cost (~$230 USD) lab-constructed GPS and accelerometer livestock collars. Objectives of this research were to 1) develop a classification algorithm to discriminate between graze and non-graze behaviors using a combination of metrics derived from a high frequency accelerometer motion sensor and a GPS data logger and 2) assess the accuracy of the classification algorithm using model error rates and expected livestock behavior patterns.

2. Methods

2.1. Study site

Research for this study occurred at the South Dakota State University Cottonwood Field Station, which is located in the Northern Great Plains mixed-grass prairie (43.989107 N, −101.857228 E). Elevation at the station ranged from 710 m to 784 m. Soils of the mixed-grass prairie research pastures are predominantly clays developed from the Pierre formation (shale). Major soils underlying the research pastures are Kyle, Pierre, and Nunn (USDA NRCS 2018). Major vegetation includes western wheatgrass (*Pascopyrum smithii* (Rydb.) A. Love), green needlegrass (*Nassella viridula* (Trin.) Barkworth), buffalograss (*Bouteloua dactyloides* (Nutt.) J.T. Columbus), and blue grama (*Bouteloua gracilis* (Willd. Ex Kunth) Lag. Ex Griffiths). Climate of the station is characterized as an arid cold steppe (Beck et al. 2018). Long-term average (1981–2010) annual precipitation for the area is 432 mm (NOAA 2018).

2.2. GPS collar

The livestock tracking collars used in the study were constructed using a GPS data logging device and a high frequency accelerometer. The iGotU GT-120 GPS logger (Mobile Action Technology, New Taipei City, Taiwan) as described by Knight et al. (2018) was used to measure animal location. The GPS logger was programmed to collect a fix (latitude/longitude) at 1-minute intervals. Average time to acquire a fix was 1 min and 22 s. Potentially erroneous GPS fixes were cleaned from the dataset by removing all waypoints exceeding 84 m/min travel speed between successive fixes as well as fixes recorded outside a 10 m buffer from the experimental pastures' boundaries. A 3-axis X16 mini accelerometer manufactured by Gulf Coast Concepts, LLC (Gulf Coast Data Concepts, LLC, Waveland, MS) was used to measure livestock movement. Accelerometers measure acceleration forces in three directions: X, Y, and Z. Accelerometers were programmed to collect data at 12 Hz (corresponding to approximately 12 records per second, or 1,036,800 data points/day). Data from the accelerometer was stored on an onboard 8 GB micro SD card. The GPS logger and accelerometer were powered by separate 5200 mAh lithium ion batteries to extend the time-window for data collection in the field (>50 days). The accelerometer was bolted to a PVC plate, cut to fit tightly within a Pelican 1020 micro-case (Pelican Products Inc., Torrance, CA) to prevent movement of the accelerometer within the case and to provide protection from weather. The GPS logger and batteries were secured to the PVC plate using Velcro straps (Fig. 1). Pelican cases were fixed to nylon cow collars and were positioned on the animal so the sensors would be resting at the bottom of the animal's neck. The weight of the case was sufficient that it remained positioned at the bottom of the neck for the duration of the season.

2.3. Data collection

Data collection occurred over a three-year period from 2016 to 2018. Yearling steers grazed four pastures from May to August in 2016 and 2018, and from May to July in 2017. The shorter grazing season in 2017 corresponded with a drought year; cattle were removed early from the pastures to prevent damage to vegetation. The research project was overlaid on an existing long-term grazing study on the Cottonwood Field Station (Dunn et al. 2010). Pastures were dominated by cool season mid-grasses (e.g. western wheatgrass and green needlegrass) with shortgrass understory. Five steers within each pasture were outfitted with the GPS tracking collars at the beginning of the grazing season. Animals were

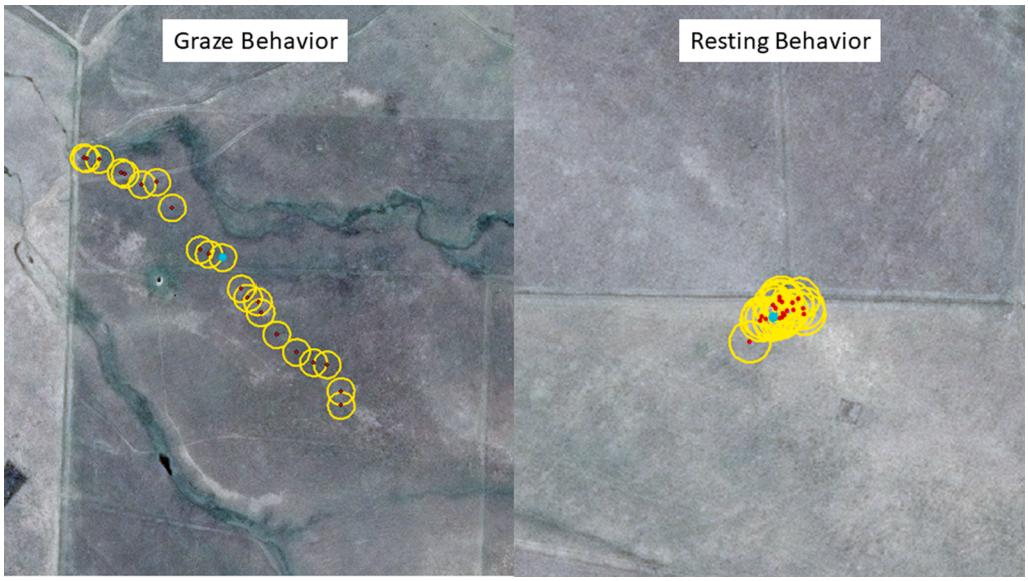

Fig. 2. Examples of data windows for calculating metrics derived from the GPS device. For each example, the highlighted blue point is the fix of interest (FOI) point. Each red point is a GPS fix within the 21-point window (comprised of the FOI and 10 fixes prior and 10 fixes after the FOI) and the yellow circles represent a 10 m radius around each GPS fix. **Graze Behavior Example:** The FOI for the graze behavior has a count of 1 because only one point in its 21-point window fell within a 10 m radius of the FOI. The FOI has a sum of 32 based on the sum of the counts for each point in the 21-point window. **Resting Behavior Example:** The FOI for the resting location has a count of 13 because 13 points in the 21-point window fell within 10 m of the FOI; the sum of the counts for all points in that FOI's 21-point window is 232. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

gathered into corrals once during the grazing season (after approximately 45 days) to download data and charge batteries.

2.4. Field observations

Direct visual observations in the field were recorded to link accelerometer and GPS data to livestock behavior. There were 3 observers in 2016, two in 2017, and two in 2018. All observers were trained to recognize and record changes in different livestock behaviors. During field observation days, an animal within a pasture was selected at random for observation. Animal ID and animal behavior was recorded to the nearest minute. Changes in behavior were recorded if an activity lasted more than one minute. Initial behaviors recorded included grazing, walking, standing, ruminating, and drinking. Typical duration of observations lasted 2–4 h, and a total of 8 h of field observations were attempted each week depending on observers' availability. For analysis, all behaviors were grouped into two categories, graze (graze) or non-graze (walking, standing, ruminating, and drinking) behaviors. Field observed behavior was then assigned to the corresponding date time stamp for that animal's GPS collar. The total number of observed GPS/accelerometer data points by year was 3340 for 2016, 1093 for 2017, and 828 for 2018, with a combined total of 5261 observations over three years. A total of 45 individual animals were observed over the three-year period. Observations were used to construct a training dataset for statistical analysis.

2.5. Data processing

Accelerometer and GPS data were merged using a two-step approach in Python (Python Software Foundation). In the first step, accelerometer data was aggregated to 1 s intervals to reduce data size. Data metrics from the accelerometer included the X, Y, and Z axes, and additional calculations of movement intensity ($MI = \sqrt{X^2 + Y^2 + Z^2}$) and signal amplitude ($SMA = |X| + |Y| + |Z|$) (Campbell et al., 2013; Tatler et al., 2018). For each one second interval, mean, maximum, minimum, and standard error were calculated for X, Y, Z, MI, and SMA measurements. Thus a total of 20 variables were calculated from the accelerometer output. In the second step, accelerometer data was merged with the GPS data by identifying all 1 s time stamps that fell between successive GPS fixes, and calculating the average of the accelerometer variables for that time period. For example, if the GPS recorded a fix at 06/01/2016 12:13:14 and the next fix was recorded at 06/01/2016 12:14:36, all accelerometer time stamps that fell between those time intervals would be averaged and allocated to the 06/01/2016 12:14:36 timestamp. GPS timestamps were corrected for local time (Mountain Standard Time) to ensure correct pairing of accelerometer and GPS data as well as pairing with livestock observations made in the field.

Three additional metrics were calculated from the GPS fix locations to aid in behavior classification. These included the rate of travel between successive fixes (m/min), a count variable, and a sum variable. The count and sum variables were calculated using a moving window algorithm to loop through the GPS data. These metrics were calculated to help capture some of the movement patterns associated with animals traveling or remaining stationary based on GPS location data. For every GPS fix, a 21-fix window (made up of the fix plus the 10 fixes prior and the 10 fixes after) was created for that fix of interest (FOI). This corresponds roughly to a 30-minute time window due to the average length of time to acquire a fix (1 min and 22 s). For each fix in a 21-fix window, including the FOI, the number of other fixes within that window that are within a 10 m radius was determined as that fix's count. The count variable for any fix, including the FOI, had a maximum value of 20 (reached only if all other fixes in the 21-point window for the FOI were within 10 m of a given fix). The sum variable for each FOI was calculated by summing the counts for all fixes in the 21-point window (max = 400). An example can be seen in Fig. 2.

2.6. Statistical analysis

Four classification algorithms were selected to predict behavior and included Random Forest (RF), Linear Discriminant Analysis (LDA), Quadratic Discriminate Analysis (QDA), and support vector machines (SVM). Livestock behavior (G or NG) was the response variable and metrics derived from the accelerometer and GPS devices were the predictors (23 total). The datasets used to build these models included only those data for which observational, GPS, and accelerometer data were available. Algorithms were used to classify behavior as either graze (G) or non-graze (NG). To test the accuracy of each model, a validation set approach was used by randomly splitting each dataset into an 80% training, 20% test dataset. Yearly models were constructed for 2016, 2017, and 2018 as well as a combined global model that included data from all years. Identical train and testing datasets were used to test classification accuracy for each algorithm. All analyses were conducted

Table 1
Model error rates (%) from the random forest (RF), linear discriminate analysis (LDA), quadratic discriminate analysis (QDA), and support vector machine (SVM). The validation set error rate is the result of reserving 20% of the data to calculate test error rates. The global model is a combination of 2016, 2017, and 2018 data. Data were derived from yearling steers outfitted with GPS/accelerometer collars in four pastures grazing summer range in South Dakota from 2016 to 2018.

Year	RF	LDA	QDA	SVM
2016	11.5	16.7	14.6	13.7
2017	6.4	4.1	8.2	6.4
2018	14.4	19.9	20.4	11.4
Global	11.2	13.9	15.3	11.6

using the Comprehensive R Archive Network (CRAN).

LDA and QDA analysis was performed using the 'MASS' package in program R (Venables and Ripley 2002). For the RF model, the 'randomForest' package implemented by Liaw and Wiener (2002) was utilized. The random forest models were built using 10,000 decision trees and the default number of nodes at each split. The 'e1071' package was utilized to train the SVM algorithms (Meyer et al. 2006). SVM model tuning was performed prior to classifying test data. Linear, radial, and polynomial kernels were tuned using a grid search method and 10 fold cross validation to estimate cost (all kernels), gamma (radial), and degree (polynomial) parameters. SVM models were tuned separately for each year and the global dataset. The SVM model with the lowest cross validation error rate was selected to predict accuracy on the test dataset.

Following the model testing and validation stage, a final predictive model was selected based on the lowest classification error rate. The final model was constructed using all available data. The final model was used to predict animal behavior for all un-observed observations for the GPS collared steers. As a secondary assessment of model accuracy, predictions were then used to calculate daily time spent grazing, and to generate histograms of number of graze fixes per hour of day for each animal.

3. Results and discussion

3.1. Algorithm selection

Algorithm classification error rates can be seen in n Table 1. Overall the RF and SVM models performed better than the LDA and QDA, with exception to the LDA in 2017. Higher performance of the RF and SVM models may be due to a better ability to predict outlier data. Overall, 2017 had the lowest error rates compared to the 2016, 2018, and global models. Results from this study indicate that combining training data across years led to lower misclassification rates in two out of three years for the RF and LDA models. Augustine and Derner (2013) reported a cumulative year model had a lower misclassification rate in three out of four years compared to individual yearly models using a classification tree approach. One disadvantage to using non-parametric classifiers such as RF and decision trees is that they require a large number of observations to accurately estimate the mapping function (James et al. 2014); improved performance in cumulative yearly models are thus likely the result of incorporating more training examples in the fitted models.

Model tuning for the SVM selected a radial kernel with a cost of 100 and a gamma of 1 in 2016, a linear kernel with a cost of 1 in 2017, a radial kernel with a cost of 100 and a gamma of 0.5 in 2018, and a polynomial kernel with a cost of 3 and degree of 3 for the global model. One of the benefits to selecting a RF algorithm is the ease of implementation reducing the need to parameterize models, saving computational time. The RF model slightly outperformed the SVM model when classifying the global test dataset. Comparisons between test dataset predictions for the global dataset resulted in a 95.3% agreement between the RF and SVM models. Previous research classifying sheep behavior from accelerometer data has shown random forest to outperform SVM and other classification algorithms (Mansbridge et al. 2018). Due to the lower error rates and increased efficiency in implementation, the RF model was selected to classify all unobserved data. For the global RF model, training (out of bag (OOB)) error rate was 10.86%, and comparable with the test error rate (Table 1). Similarity in model accuracy between the train and test datasets indicated that the RF models were not overfitting or underfitting in any year. Out of Bag (OOB) accuracy in random forest models is considered an unbiased estimate of the overall classification accuracy (Breiman 2001).

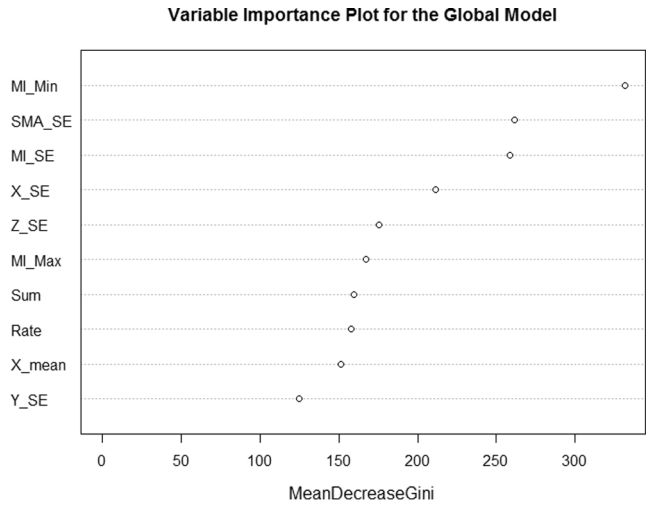

Fig. 3. Final random forest model variable importance plot. Model was generated using all available observation data from 2016 to 2018. The plot represents the top 10 (out of 22) predictors that contributed the most to model accuracy. Variables used in the model include the mean, maximum (Max), minimum (Min), and standard error (SE) calculated for X, Y, Z, movement intensity (MI), and signal amplitude (SMA) measurements as well as the rate of travel, sum, and count variable derived from GPS data.

3.2. Accuracy rates

Higher accuracy rates (>90%) for classifying livestock behavior with accelerometers have been reported using a variety of classification algorithms. For example, Mansbridge et al. (2018) reported an overall accuracy of 92% using the random forest algorithm to classify sheep behavior, and Giovanetti et al. (2017) reported a 93% accuracy rate using stepwise discriminant analysis to classify sheep behavior. Similar higher classification accuracies have been observed in classifying cattle behavior with accelerometers (Dutta et al. 2015, Gonzalez et al. 2015, Tamura et al. 2019). Lower classification accuracy rates in our study compared to previous work may be due to differences in both the duration of the trials and scale of paddocks allowed to graze. For instance, Tamura et al. (2019) reported an accuracy of 99% in classifying dairy cattle behavior from accelerometers, however cattle behavior was only observed over a 6-hour period in free stall barns in this study. Dutta et al. (2015) monitored dairy cattle grazing perennial ryegrass pastures over a 9-day period and Gonzalez et al. (2015) monitored yearling steers grazing a 15-ha paddock over a 10-day period. Giovanetti et al. (2017) recorded sheep behavior over a longer 6-week period, however, behavior observations were monitored when animals were confined to a 20 × 20 m enclosure, and Mansbridge et al. (2018) recorded behavior when sheep were kept in a 0.12 ha paddock. In our study, observations were recorded over several months during a 3-year period utilizing 3 different herds of yearling steers continuously grazing heterogeneous rangelands in pastures ranging in size from 51 to 74 ha. Lower accuracy rates in our models compared to previous research may be due to greater variability in behavior due to observing cattle under

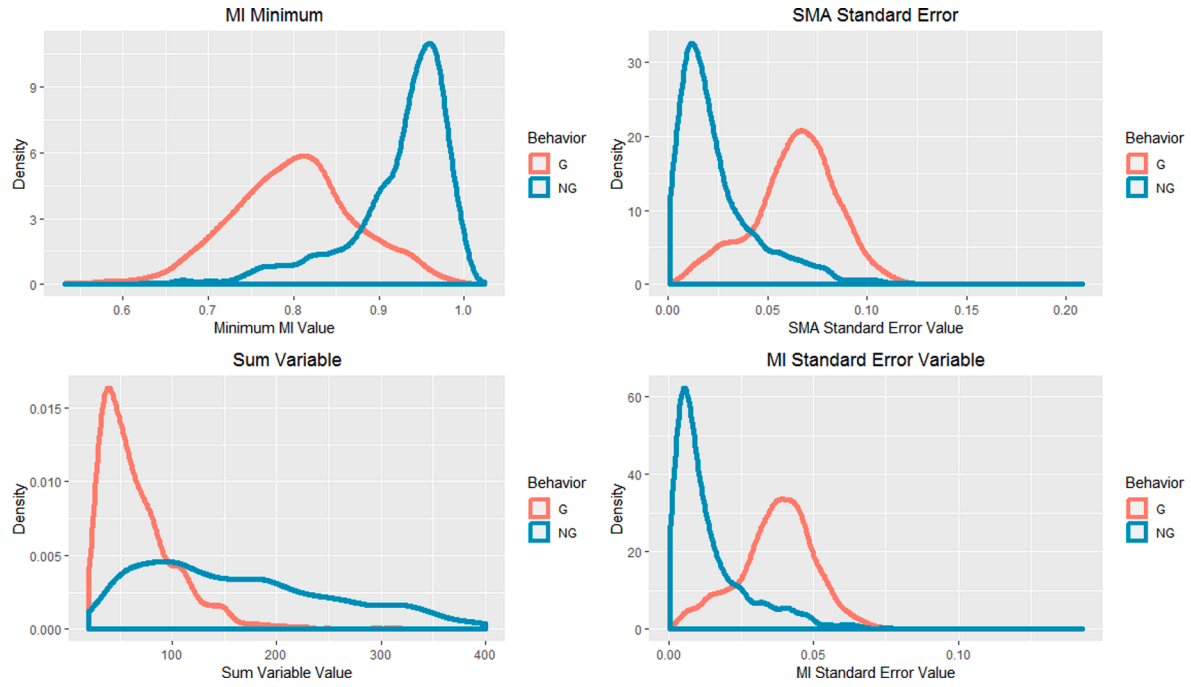

Fig. 4. Density distribution plots comparing graze (G) and non-graze (NG) behaviors. Plots derived from accelerometer movement data include movement intensity (MI) minimum, MI standard error, and signal amplitude (SMA) standard error. The sum variable plot is derived from the GPS movement data.

more natural conditions.

3.3. Accelerometer and GPS variable importance

The variable importance plot (Fig. 3) indicated the top 10 most important variables for discriminating graze and non-graze behaviors in the global model. Of particular interest was that five of the most important variables included the standard error (SE) metrics derived from the accelerometer. Density plots (Fig. 4) of SMA and MI standard error values indicated that larger standard errors were associated with grazing behavior. Additionally, the rate of travel and the 'sum' metric derived from the GPS device are also within the 10 most important variables in the model, demonstrating the utility of combining metrics from both the GPS and accelerometer.

Previous research has shown that probability density functions for the standard deviation of the X-axis (up-down head position) have 3 distinct populations representing three activity levels, with the largest standard deviation associated with foraging and traveling behavior (Gonzalez et al. 2015). In his review of cattle behavior, Kilgour (2012) indicated that 90–95% of an animal's day is allocated to grazing, resting, and ruminating with the majority of rumination happening while the animal is lying down. Higher standard error rates associated with grazing behavior are likely due to the greater amount of movement occurring for this behavior compared to lying down and ruminating. Gonzalez et al. 2015 also suggested that the use of finite mixture models may be used in place of behavioral observations for unsupervised classification under different experiments or environmental conditions. Finite mixture models can be used to determine if datasets have arisen from separate populations. The plots in Fig. 4 suggests bimodal distributions for many of the accelerometer metrics, which may be modeled using density estimation techniques to determine breakpoints in the dataset for data splitting.

Incorporating additional GPS movement data to predict livestock behavior should be viewed as complementary to accelerometer data and can potentially improve model performance. Augustine and Derner (2013) reported distance traveled between successive fixes to be one of the most important variables in classifying cattle behavior. Rate of travel may also aid in discriminating between resting and grazing behaviors, but also walking behavior (classified as non-graze) due to faster travel rates. The 'sum' metric derived from this study was likely important in identifying large GPS point clusters associated with long periods of animal inactivity. Greater importance in the model for the 'sum' metric versus the 'count' metric may be due to the 'sum' metric incorporating data from the entire moving window of GPS fixes, which would help identify resting locations for points that bounced outside a point cluster due to GPS sampling error.

Table 2
Average daily grazing time (hours) followed by standard errors. Yearling steers outfitted with GPS/accelerometer collars in four pastures grazed summer range from 2016 to 2018. Daily grazing time was calculated for each collared steer, and averaged for each pasture and year.

Pasture	2016	2017	2018
2	9.74 ± 0.05	10.49 ± 0.07	8.84 ± 0.06
3	8.74 ± 0.06	9.71 ± 0.1	8.92 ± 0.09
5	9.68 ± 0.05	8.72 ± 0.14	8.67 ± 0.154
6	9.31 ± 0.05	9.47 ± 0.1	9.08 ± 0.17

3.4. Grazing behavior predictions

Previous research classifying livestock behavior with accelerometers tended to focus on model selection, parameterization, resampling methods, and error rates (Dutta et al. 2015, Gonzalez et al. 2015, Alvarenga et al. 2016, Mansbridge et al. 2018, Rahman et al. 2018, Tamura et al. 2019). Less focus has been placed on assessing whether model predictions accurately reflect expected livestock behavior. Over the duration of this study, average daily grazing time ranged from 8.67 to 10.49 h per day (Table 2). In his review of the literature, Kilgour (2012) found that cattle spend between 6.8 and 13 h grazing per day depending on forage quality and quantity. Given that steers in this study were grazing good to excellent quality range vegetation at moderate stocking rates, average daily time spent grazing was consistent with expectations. Low standard error rates and consistency across pastures and years demonstrated that predictions from the final RF weren't over- or under-inflating grazing time estimates for different individuals or

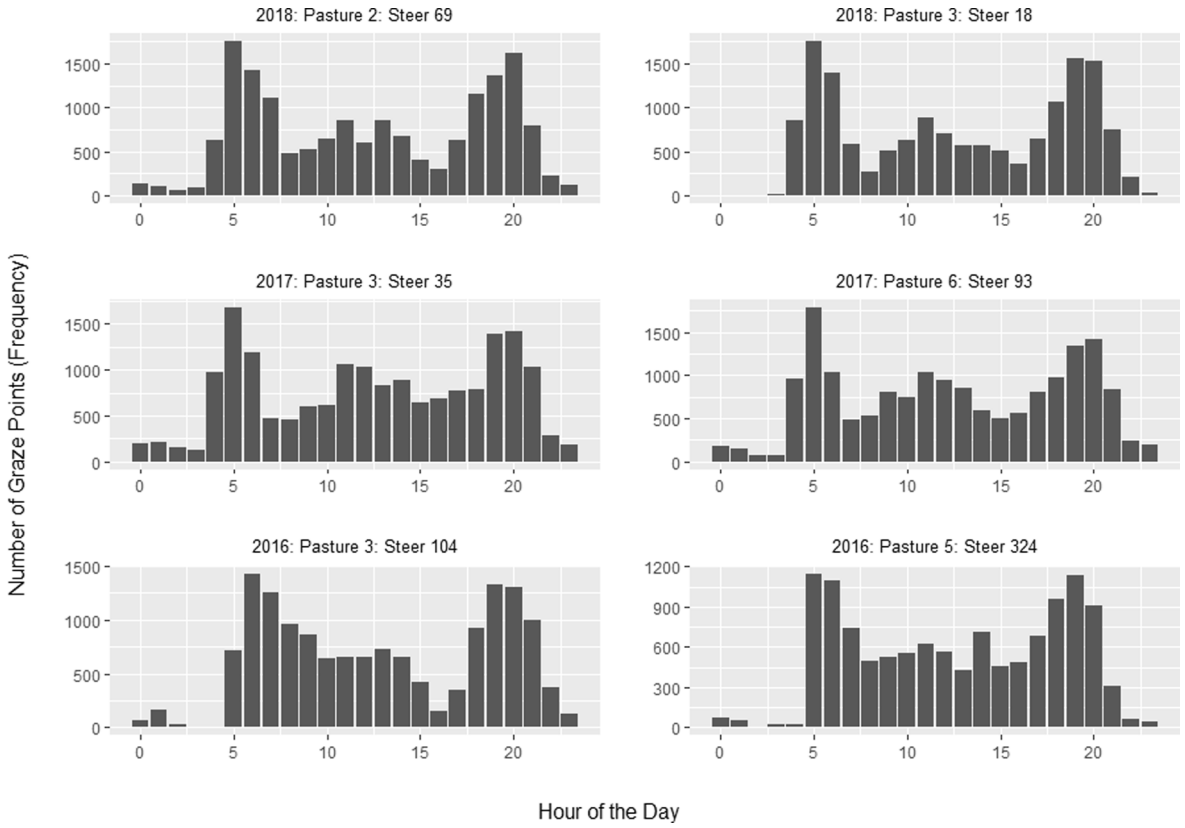
2018: Pasture 2: Steer 69
2018: Pasture 3: Steer 18
2017: Pasture 3: Steer 35
2017: Pasture 6: Steer 93
2016: Pasture 3: Steer 104
2016: Pasture 5: Steer 324
Number of Graze Points (Frequency)
Hour of the Day

Fig. 5. An example of diurnal grazing patterns from six steers outfitted with GPS/ accelerometer collars. Histograms were generated by counting the number of graze points for each hour of the day (0–23) over the duration of collar deployment (~6 weeks).

groups of animals.

Diurnal patterns of cattle behavior were assessed by generating histograms for each collared steer to show the distribution of grazing points by hour of day for the duration of collar deployment. Example randomly selected steer plots (Fig. 5) showed peaks in livestock grazing behavior at sunrise (~0500) and sunset (~2000) with intermittent grazing throughout the day and little to no grazing during night-time hours. Similar diurnal grazing patterns have been observed by Zemo and Klemmedson (1970) who reported two major periods of grazing associated with daybreak and late afternoon/evening. Likewise, Sneva (1970) reported two major grazing periods from 0500 to 0700 and 1700 to 2000, with intermittent grazing in between. While estimating model error rates and predictive power gives statistical validity to classification models, assessing whether predictions align with expected livestock behavior can serve as an important secondary tool to assess model accuracy. Diurnal plots for all animals can be seen in Fig. S1 in the supplemental materials.

4. Conclusions

The results of this study demonstrated that a low-cost, non-commercial, lab-constructed GPS/accelerometer collar can be used to accurately monitor season-long livestock grazing behavior, and that model predictions align with expected livestock grazing behavior. One of the largest challenges to monitoring season-long livestock behavior using accelerometers is managing the large volume of data generated. Recording accelerometer data over a 90-day period at 12 Hz frequency generated 93,312,000 data records, with an additional ~129,000 one minute GPS records that need to be merged per collared animal. Python code included with this study is meant to help researcher's analyze large accelerometer datasets and merge them with associated GPS data, significantly reducing processing time. Additionally, collecting field observations to validate behavior can be expensive and time consuming. Density plots shown in Fig. 4 suggest that techniques like finite mixture models may be applicable for modeling bimodal data distributions allowing for unsupervised classification of accelerometer data and warrants future investigation. Further research is needed to determine the stability of model predictions between different classes of animals (e.g. yearlings vs. cow-calf pairs) or across various plant communities. Though the focus of this study was to differentiate between graze and non-graze GPS locations to better understand forage selection on the landscape, this technology can potentially be used to answer a number of questions relating to livestock production, performance, and behavior.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2020.105957.

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